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Lost in translation: Collecting and coding data on social relations from audio-visual recordings

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ABSTRACT

Some of the constitutive features of social relations fade from view when information naturally produced by sequential social interaction is translated into network ties. Building on core concepts and ideas developed within conversation analysis, in this paper we argue that this happens because the sequential, multimodal and embodied character of social relations can be fully understood only with reference to the sequential constrains that are generated by – and at the same time shape the micro-dynamics of social interaction. We suggest that the translation of social interaction into social networks precludes analysis of the multiple interfaces that sustain social relations (multimodality), and the material resources around which social relations are organized (embodiment). We highlight audio-visual recording as a data collection technology that facilitates storage, retrieval, and analysis of complex information on social relations that is typically absent from social network data. An illustrative video-supported case study based on the observation of social and task-related interaction among members of surgical teams provides the empirical context that supports and motivates our general reflection on network data collection strategies and technologies to study social interaction. The analysis highlights the need for social networks research to return to the study of social relations.

1. Introduction

A new vision of social structure as a "living flow that reproduces," involving multiple "trajectories and movements through space-time" (Padgett, 2018: 406–407) is emerging that emphasizes the developmental, contingent, situational nature of social relations.

During the last two decades, this vision has progressively come into sharper focus, and is now changing the way we think about social networks not as sets of clearly defined nodes and ties (Butts, 2009), but rather as fluid relational systems shaped by conversational processes and discursive practices (Gibson, 2005; Mische and White, 1998). More or less explicitly, contemporary empirical research inspired by this vision, attempts to specify the link between social structure and social relations in terms of time-ordered sequences of directed relational events – or, in other words, in terms of interconnected time-dependent "trajectories" (Amati et al., 2019; Butts, 2008; Padgett, 2018).

One research domain where this broad theoretical vision is introducing significant elements of empirical innovation, is the study of small groups and teams (Butts, 2008; Butts and Marcum, 2017) – social formations that are increasingly represented and understood in terms of the time-ordered sequences of directed actions connecting participants (Leenders et al., 2016). This is particularly the case in organizational settings where, alike conversation, social interaction among participants takes place in deliberative situations (Gibson, 2012). Similar to conversation, social interaction in these contexts becomes a process of production of possibilities – for problems to meet solutions (Cohen et al., 1972), and for current actions to be connected to past discussions and decisions (Gibson, 2011). How could information on the (directed) social relations and the (undirected) individual behaviors of participants in this production process be collected and organized into a coherent empirical observation scheme? The main contribution of this paper is to offer a possible answer to this question.

The specific opportunity to do so, is provided by an ongoing empirical research project on surgical teams – a setting that illustrates with particular clarity how social relations emerge from task-oriented directed behavior unfolding in continuous-time (Zheng et al., 2009; Zheng and Swanström, 2009). Because of the sequential, embodied and multimodal character of interaction among participants during surgery, the study of surgical teams demonstrates the need to rethink the conceptual link between social relations, produced by the lack of

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independence among social agents (Pattison and Robins, 2002), and social networks (Butts, 2009).

The illustrative case study that we develop in the empirical part of the paper, is based on a short excerpt from a complete video recorded history of an actual surgery (Korkiakangas et al., 2016). The full dataset at our disposal contains footage on twenty distinct surgical operations performed in two operating theatres at a major teaching hospital in London (Bezemer et al., 2016; Korkiakangas et al., 2014; Korkiakangas, 2016; Weldon et al., 2013, 2015). Various types of operations were recorded (i.e., laparoscopic and open operations in general, gastro intestinal, and bariatric surgery) producing over 68 h of film, or 34 h in operating time. The choice of surgical technique (open or laparoscopic) was dependent on a mixture of the patient's circumstances, the surgeons' preference, and the evidence-base for best outcome. Coordination among team members (surgeons, nurses, anesthetists, and operating department practitioners) is achieved through various forms of interaction reflecting a complex mix of verbal and non-verbal, directed and undirected, reactive and autonomous behaviors shaped by multiple sequential constraints. We discuss how audio-visual recording represents perhaps the only technology available that may be capable of transforming these concurrent expressions of coordination connecting members in task-oriented teams in reliable sources of relational data amenable to empirical analysis (Christianson, 2018; Nassauer and Legewie, 2018; LeBaron et al., 2018).

The paper proceeds as follows. The notion of temporality and its implications for the study of social interaction is the focus of Section 2. We discuss how a detailed understanding of social processes - such as coordination - requires a focus on the sequential nature of social interaction and its compounding features of multimodality and embodiment. In Section 3 we discuss how an increased awareness of the timing of social processes should be reflected in the type of relational data that are collected, as well as in the methods for collecting these data. We describe, in particular, the advantages of using audio-visual recordings as valuable sources of information producing richer and more detailed data amenable to network analysis. In sections 4 and 5 we describe the empirical case. We illustrate how continuous-time social interaction data may be extracted from video recordings, and coded as relational events connecting team members. Section 6 concludes the paper by discussing opportunities and challenges for future research on social relations and social networks.

2. Lost in translation: from social interaction to social networks in the analysis of small groups

Social interaction events among members of small groups may be observed directly. Their analytical reconstruction - social networks - typically, cannot. In consequence, studies of social relations are rarely based on direct observations. Historically, social networks research has frequently been based on the assumption that samples of social interaction events (e.g., telephone calls) are representative of long-term structural patterns of ties (e.g., friendship), and then focused on the latter, while ignoring the former (Freeman et al., 1987). With few recent exceptions (Kitts et al., 2017), this assumption typically remains implicit in empirical studies.

While models for social networks are becoming progressively more statistically sophisticated, analytically detailed, and mathematically complex, our understanding of social relations remains based on time-honored theoretical frameworks such as, for example, status characteristics (Berger et al., 1972), social exchange (Blau, 1964, 2017), and balance (Heider, 1946). Because these classic equilibrium narratives rarely provide specific indications about the timing of the relational mechanisms they postulate, empirical studies inspired by these theories are almost invariably based on analytically reconstructed social networks of (friendship and advice) social "relations" (Krackhardt and Kilduff, 1999; Lazega et al., 2012; Torlò and Lomi, 2017) – rather than observed social interaction as it unfolds across multiple time scales. What is lost in this translation of "social interaction" into "social networks"?

One recent answer to this question emphasizes the loss of information on the temporal micro-structure of social interaction induced by aggregate network representations (Butts, 2008, 2009). This argument is directly relevant both to the way we understand face-to-face interaction within team and small-groups (Butts and Marcum, 2017; Pilny et al., 2016; Leenders et al., 2016), as well as large-scale technology-mediated interaction in virtual teams (Lerner and Lomi, 2019). Echoing innovation in micro-sociological studies of social interaction inspired by conversation analysis (Gibson, 2003, 2005), current research on small group interaction has recognized the importance of sequentiality, and the related need to develop observation schemes capable of maintaining information about the timing of interactive turns in which team members are engaged (Leenders et al., 2016). While we recognize the importance of sequentiality, in the context of this paper we focus on why the temporal micro-structure of social interaction is important, and what are the research design consequences of taking it seriously in the study of coordination within task-oriented teams in organizations.

Developing further the conversational and linguistic turn in the analysis of social interaction (Gibson, 2000, 2008), we elaborate on Mondada (2019) to highlight two general characteristics of small-group interaction and coordination that give importance to sequentiality: multimodality, and embodiment. Our central argument in this paper is that these essential elements of social interaction help to identify where the action – and social interaction actually are.

Central in conversation analysis, the concept of multimodality has been introduced to go beyond the traditional distinction between verbal and non-verbal behavior which does not do justice to the diversity and complexity of interfaces sustaining social interaction in small groups (Mondada, 2016). Additional channels such as, for example, prosody, gestures, gazes, and body postures and movements are also essential components of social interaction. For example, in the context of surgical teams that we discuss later in this paper, a scrub nurse can anticipate an instrument request from a surgeon's arm movement alone, and the instrument frequently changes hands without verbal communication (Bezemer et al., 2011a, 2011b). As Mondada observes, the fact that coordination in surgical team is: "realized by a complex multimodal gestalt constituted by verbal and gestural/visible resources, challenges not only the analysis but also the representation of data" (2014: 138). Social network data that are usually collected to study coordination in task-oriented teams in organizations typically do not contain information on naturally occurring episodes of multimodal communication among team members (see, for example, Reagans and Zuckerman, 2001). Multimodal communication requires attention to the sequential ordering of social interaction events. Communication through one interface (e.g., gestural) changes its meaning depending on its position in a time-ordered sequence of prior communication events connecting a sender and a receiver through a different interface (e.g., verbal). Inferences that the unimodal communication data that are typically collected can sustain tend to be limited to generic kinds of communication (e.g., "advice") occurring on conventionally defined channels.

Embodiment refers to the variety of objects such as "artifacts, tools, technologies, and documents" (Mondada, 2019) constituting the world of material resources necessary to sustain social interaction, around which social interaction is organized, and through which it becomes observable. As we note in the context of the empirical case that we develop later in the paper, one of the most central collaborative tasks during surgical operations involves the passing of surgical tools and instruments. Little is known about how nurses and surgeons achieve coordination (Korkiakangas et al., 2014). Clearly, association between individuals through passing and sharing of objects and artifacts does not lend itself easily to a conventional two-mode network representation. These associations are instantaneous, contingent (need-driven), repeated, intermittent and, often, ambiguous. These are all characteristics of social interaction that are not typically associated to network "ties" reconstructed as unambiguous enduring "states" occupied by connected actors (Butts, 2008; Stadtfeld and Block, 2017). As Mondada recently put it (2019: 50), embodied objects that sustain social interaction: "Are not approached per se, as static materials in isolation, but as they are mobilized moment by moment in relevant and timed ways within a course of action." Clearly, the sequential order of embodied interaction – i.e., interaction sustained by, and organized around material objects – matters greatly in surgical teams where the order of interaction among members is defined by professional best practices. Understanding the ecology of social interaction emerging from the dual association of individuals and material objects (Breiger, 1974) requires careful reconstruction of the spatial arrangements and locations both of the objects as well as people within and across interaction settings. As we will see in greater detail in the empirical part of the paper, the position of the surgery tools relative to the position of surgeons and nurses has detectable implications for the quality of surgery processes and outcomes (Bezemer et al., 2016).

As this general discussion makes clear, we are not the first to identify multimodality and embodiment as constitutive characteristics of small group interaction. However, their implications for how we observe and understand social interaction in small task-oriented teams – and hence their implications for how we represent social networks – have not yet been carefully examined. We are also not the first to emphasize the analytical potential of audio-visual technologies to record and organize "naturally occurring data" (Lynch, 2002; Speer, 2002) produced by continuous-time individual behavior (Collins, 2009), and the propensity of these technologies to alleviate problems posed by multimodality and embodiment in the study of social interaction (Mondada, 2008; LeBaron et al., 2018). Our work may be best understood as part of a new wave of studies (recently reviewed in Nassauer and Legewie, 2018) relying on video recordings technologies to uncover causal micro-mechanisms underlying observed individual behavior. The contribution of our work to this emergent literature involves linking naturally occurring social interaction data to the analysis of relational event sequences in the context of an analysis of small task-oriented teams in organizations.

3. Audio-visual data

The collection and analysis of visual data have a long history in disciplines such as sociology, psychology, anthropology, and criminology– to name but the most common fields of inquiry (Nassauer and Legewie, 2018; Margolis and Pauwels, 2011). In these and related domains of social research, visual data have been collected to study a broad range of phenomena, such as group dynamics and cooperation (Burtscher et al., 2010), family interactions (Waldinger et al., 2004), the evolution of social life and segregation in urban spaces (Hampton et al., 2015), and episodes of interpersonal and collective violence (Collins, 2009). The surge in the use of visual data has been greatly stimulated by the increasing availability of widespread recording devices, including smartphones, closed-circuit television (CCTV), body cameras and even drones to record real life, social situations, and personal interactions. In all these cases, the measuring devices are integrated into everyday objects facilitating the collection of data on naturally occurring behaviors (Barakova et al., 2013).

Development of new analytical frameworks and approaches for the analysis of visual data has accompanied the evolution of technological possibilities (Mathur et al., 2012). Interaction between developments in data collection and analysis is blurring the traditional boundaries separating quantitative and qualitative research designs (Saint-Charles and Mongeau, 2018). This confusion between quantity and quality is generating considerable interest in the new research possibilities offered by audio-visual data. As an example of this interest, the recent special issue of Organizational Research Methods (2018) on video data in organizational research was conceived to advance our understanding of the advantages and challenges of using a research design approach based on video data to study a wide array of phenomena involving individuals and teams in organizations.

In particular, video-based research may assist in responding to the call for a more comprehensive approach to research design in the study of social network – one that combines qualitative and quantitative methods in new and innovative ways (Edwards, 2010; Basov, 2018). Video data offer a distinctive approach to collecting rich real-time data that might subsequently support quantitative social network analysis (Christianson, 2018; Nassauer and Legewie, 2018). The joint reliance on qualitative information extracted from video data and quantitative network analysis offers new promises in the study of meaning associated to observed social processes, and might contribute to a more interpretive understanding of the social phenomenon at hand (Fuhse and Mützel, 2011).

LeBaron et al. (2018) discuss the main similarities and differences between the collection of video data and other data collection approaches, such as direct observation, archival sources, participant observation, interviews and surveys. Video recording is increasingly becoming a data collection tool for researchers interested in the multimodal character of social interaction (Jewitt, 2012): It provides a fine-grained record of social interaction events detailing gaze, expression, body posture, and gesture as they unfold sequentially (LeBaron et al., 2018). As suggested by Nassauer and Legewie (2018), by observing a person's movements, uses of space, interactions, exchanges of glances and gestures, facial expressions, and body postures, it is possible to identify patterns that explain social processes of interest. Other than the multimodality feature of social interaction, the use of video recordings also allow to examine social interactions as embedded within, and affected by material environments, where physical objects, artifacts, tools and technologies abound (LeBaron et al., 2018). This is the embodiment (or materiality) feature of social interaction.

In the specific context of task-oriented teams – the context of our empirical illustration -, video recordings enable the collection of high-quality data on how team members interact to coordinate their action at any given point in time, and the analysis of the consequences of these interactions for team outcomes (Nassauer and Legewie, 2018). An ideal context to illustrate the advantages of using audio-visual data is provided by surgical teams.

4. The use of video data for studying surgical teams

Over the past fifteen years, the progressive diffusion of video recording technologies and the reduction in their cost, have made the collection and use of video data increasingly common in the study of a wide array of medical procedures, including surgery (Weldon et al., 2013). The focus of video research conducted to date in this setting has ranged from the exploration of collaborative work and effective teamwork (Randell et al., 2017; Hindmarsh and Pilnick, 2002; Zheng and Swanström, 2009), to communication failures (Lingard et al., 2004), language use, and verbal acknowledgement (Bezemer et al., 2011a, 2011b; Korkiakangas et al., 2016), object transfer (Korkiakangas et al., 2014), music playing (Weldon et al., 2015), body orientation (Moore et al., 2010), team mobilisation (Mondada, 2011a, 2011b; Korkiakangas et al., 2016) and interprofessional learning (Collin et al., 2010; Bezemer et al., 2016).

These studies of surgical teams display a wide variety of foci, and the use of video appears to have enabled a more exploratory approach to the happenings within an operating theatre, a traditionally inaccessible area of study. Findings produced by these and related studies have been valuable in revealing the complex play of communication and coordination practices within surgical teams. For example, Hindmarsh and Pilnick (2002) found that communication within surgical teams was sensitive to talk and bodily conduct, which ultimately enabled a sense of an organizational 'knowing' culture. Moore et al. (2010) identified that over time, individual team members learn to

Table 1
Description of each surgical technique and its associated benefits.

Surgical technique	Open surgery	Laparoscopic surgery	Robotic surgery
Description of the surgical technique	A large incision is made at the site of the procedure to enable the operating surgeon direct visual and physical access.	Rather than using a large incision, laparoscopy, also known as keyhole surgery, involves using several small incisions to perform a surgical procedure. Each incision allows for extra-long instruments (controlled by a handle at the end), and a camera to be inserted into the patient. The operative field is visualized via two-dimensional TV screens placed around the operating room/theatre.	The same as laparoscopic surgery but with a robot controlled remotely by a surgeon.
Benefit of the technique	Requires less equipment and provides good visual and physical access. Also allows the surgeon tactile information.	Is less invasive for the patient with a faster healing time and decreased risk of infection. Allows other surgical team members to see the procedure in progress.	Allows for finer and more accurate movements, as well as the option for surgery to be carried out remotely (e.g. another country).

understand particular movements or bodily orientations that aid coordination efforts. How surgical team members learn together and from each other was also revealed. Zheng and Swanström (2009) concluded that working in a team allows surgeons to develop sophisticated cognition to anticipate an up-coming task and provide assistance without verbal communication, and that experienced nurses develop sophisticated cognition, with anticipatory movement and eye gaze being two valuable behavioral markers for assessing team performance (Zheng and Swanström, 2009).

To date, the body of work produced from video data has been insightful but heterogeneous due to the broad possibilities of focus, and the difficulty of obtaining video data in this particular setting. More recently, there has been an increase in the use of video-recordings of surgical teams, and a movement termed the ‘Operating Room Black Box’ (officialized by Dr Teodor Grantcharov) has commenced in Canada and is making its way to Europe (Grantcharov, 2015; Jung et al., 2018; Moulton, 2015).

Although research based on the use of video recording of surgical teams is increasing, the main focus of analysis of these particular recordings is on the technical performance of teams, and environmental and organizational factors, not social interaction practices such as communication, or teamwork. In their systematic review, Weldon et al. (2013) found that there are only a few video-based studies that elaborate on the actual, real-time cooperative behavior in the operating theatre. Where cooperative behavior has been addressed, only pre-determined factors have been measured and attended to (Jung et al., 2018; Dimick and Varban, 2015; Grenda et al., 2016). This is in part due to a lack of an appropriate framework for analyzing social interaction practices systematically, and the time and resources required to collect, code and analyze many hours of video recordings.

The advantages of collecting video data on social interaction in this setting are many and relevant (Korkiakangas et al., 2016). Video data allow a detailed examination of the series of actions individuals perform during surgical operations. Individuals perform these actions through different forms of bodily conduct, such as speech, gesture, movement, and gaze. Video data render visible how these actions are ordered as sequences: for instance, how an instrument request is made and followed by the provision of the instrument. Thus, rather than considering the actions of individuals in isolation, video recorded data allow consideration of how each individual’s behavior emerges in relation to the actions of others. Video data also render visible how action is situated within a material, physical context. For example, how the position of material objects or technologies helps, or hinders, the flow of interactions within teams. Such detailed description may be used to further the understanding of why and how particular joint tasks, such as object exchanges, are achieved and sometimes not achieved, to identify optimal and sub-optimal patterns, to link observed patterns of interactions to characteristics of teams (including performance), and to make comparison of interactional patterns across different types of surgical operations. In other words, video data allow to make visible the micro-structure of coordination and its dynamics at an unprecedented level of detail.

These micro-level dynamics may result in fundamental macro-level (i.e., group level) outcomes. For example, Lingard et al. (2004) focused on communication in surgical teams and concluded that communication failures contributed to jeopardizing patient safety, and occurred at least 30 % of the time. Communication breakdowns are the biggest factor contributing to surgical errors (Bezemer et al., 2016; Korkiakangas et al., 2014). The collection of video-recorded data allows for a more detailed and systematic study of interaction practices within surgical teams, thus providing an opportunity to identify and assess their complexity in real-time, improve work practices, and develop a better understanding of the relation between interaction practices and team performance.

5. Empirical illustration: Recording naturally occurring data

The opportunity to illustrate how audio-visual data may be collected, and organized as a mixed sequence of actions and interactions is provided by video recorded data of surgical teams in two operating theatres at a major teaching hospital in London. The data were collected over six months, in 2012–2013, through a mixed approach involving both ethnographic observation techniques supported by video recording technologies. The observation scheme focused on actual practices enacted by surgical team participants within operating theaters. A total of 20 operations (open, laparoscopic and robotic surgery – see Tables 1 and 2 for more detailed descriptions) of different length (from two to five hours) were recorded using High Definition video cameras. The cameras were positioned to capture different viewpoints in the operating theatre. Two inconspicuous RevoLabs xTab wireless microphones were also used when the camcorder microphones alone were not sufficient to ensure an adequate quality of audio recording. However, these microphones were only required for surgeons and scrub nurses (under sterile gowns) to better capture their verbal interactions when wearing masks and huddled around the patient. The recordings produced over 68 h of film (from two strategically positioned camcorders) - 34 h in operating time - of four consultant surgeons (attending surgeons), five registrar surgeons (resident surgeons), five scrub nurses, six circulating nurses, four consultant anesthetists (anesthesiologists) and five Operating Department Practitioners (ODPs). The 20 operations were recorded at random through opportunistic sampling and also included fourteen cases (70 %) that had music playing (at some point during the operation), and six (30 %) that did not have any music playing. Due to the challenges in collecting this type of data, this dataset offers a unique insight into task-oriented teams performing a procedurally diverse range of surgical operations (Bezemer et al., 2016; Korkiakangas et al., 2014, 2016; Weldon et al., 2013, 2015).

The observed – i.e., recorded – behavior is a complex set of sequences of coordinated actions and interactions among team members during the surgeries. As shown in section 5.2., actions include behaviors where a direct interaction among team members is not necessarily involved or required, such as the action of operating on patients, or

Table 2
A descriptive table of the surgical techniques used for every operation type.

Surgical technique Operation type	Open surgery	Laparoscopic
General	1 x Right inguinal hernia repair	1 x Laparoscopic internal hernia repair 1 x SILS Cholecystectomy 1 x Laparoscopic cholecystectomy 1 x Laparoscopic incisional hernia repair 2 x Staging lap and OGD 1 x SILS laparoscopic sigmoidectomy 1 x Staging lap and feeding tube insertion 1 x Staging lap 1 x Laparoscopic fundoplication
Upper-gastrointestinal	1 x Oesophagectomy	2 x Laparoscopic staging
Bariatric		1 x Laparoscopic gastric bypass 3 x Laparoscopic sleeve gastrectomy 2 x Gastric band

observing. We will code them as "actions" in our proposed coding scheme. Interactions, on the other hand, include directed behaviors where at least two, or more team members coordinate over a specific task, such as passing an instrument, or requesting assistance. We will code them as "interactions". These and other routine coordination practices, as well as their relationship with factors such as music playing, inter-professional education, team mobilization, collaboration and decision-making have been examined in a number of qualitative or descriptive studies (Bezemer et al., 2016; Catchpole et al., 2018; Korkiakangas et al., 2014, 2016; Korkiakangas, 2016; Randell et al., 2017; Weldon et al., 2013, 2015). The purpose of the illustrative coding of a small fragment of the footage at our disposal is to offer an opportunity to reflect on how qualitative data on continuously observed behaviors may be used in quantitative studies based on social network analysis. The complexity and variety of coordinated actions and interaction taking place during surgical operations allow us to illustrate the multifaceted features of social interaction data, such as their sequentiality, multimodality, and embodiment - as described in section 3 – that can be captured through video recordings (Le Baron et al., 2018; Nassauer and Legewie, 2018; Jewitt, 2012; Mondada, 2019). How can all these features accurately be taken into account when transforming qualitative information on observed behavior into numerical data?

In the next section, we suggest a possible answer to this question. With the help of a small illustrative example that we develop we show how the observed behavior may be coded as sequences of relational events involving team members. The purpose of this coding scheme is to collect detailed information on the microstructural dynamics of social interaction, by also taking into account contextual or exogenous factors, such as features of the operating theatre or team members. The coding scheme that we propose is also useful as it turns qualitative information on observed behavior into data amenable to quantitative social network analysis. We show how alternative coding practices resulting from aggregations of interactions across time and team members may result in loss of relevant information that may be needed to understand and interpret observed social interaction behaviors.

5.1. *Observing and recording behavior*

The examples we present in this section are mostly illustrative. They are based on individual episodes extracted from the larger sample of video recordings that we believe provide evidence of the presence – and also co-existence – of the features of sequentiality, multimodality, and embodiment inherent to social interaction data. The selected extracts from videos have been analyzed in previous studies involving one of the authors of this paper (SMW) who took an active role in the collection of the video data. These studies have relied mainly on qualitative approaches based on ethnography and interactional frameworks for the analysis of video data.

Example 1 is taken from Korkiakangas et al. (2016), and is used in our paper to illustrate the multimodality of social interaction. The Authors zoom in on the practice of responsiveness to requests during surgical operations. Some of the responses involve speech and some do not. A qualitative (video) analysis of communication events is performed in Korkiakangas et al.'s paper, by examining from start to finish 13 h of operations and logging every form of interactional event (e.g., request, question, repetition, response, whether response was produced verbally or nonverbally, and associated bodily conduct/position). Information on time elapses in the request-response interactions were also recorded. As the Authors discuss in the paper, the *type* and *timing* of a response can be consequential to the operation at hand.

In the case of "*Actional response*", requests are attended through some sort of physical activity. For example, the Authors report the example of a surgeon's verbal request *["Local, please"]*, that is handed out by the scrub nurse through a nonverbal action *[Scrub nurse passes dish with syringe to surgeon]* within approximately one and a half seconds. This is the time it usually takes to pick up the item and hand it over to the surgeon when the scrub nurse is already holding the item and has her body aligned with the surgeon. So verbal responses seem not to be needed when a request can be fulfilled immediately. A "*Verbal response*" may be needed, however, to acknowledge receipt of a request. The Authors report the example - also used later for developing our coding scheme - of a surgeon addressing a request to the circulator *["Gas on, please"]*, and the circulator replying with an actional response preceded by a verbal acknowledgment of the request. In the video, the circulator is momentarily out of the theatre site, in the adjacent preparation room, so she is unable to act immediately as she is called to turn the gas on. This is accounted for by her verbal acknowledgement *["Yes, coming"]* produced in response to the request. This verbal response orients to the time it would take her to reach the switch (approximately 6.5 s in the fragment) and inform the surgeon that the request, nevertheless, has been heard. Finally, the Authors discuss the example of a "*Delayed actional response*", when verbal acknowledge is missing and there is action following a request whilst remaining silent. In the fragment described in the paper, the surgeon's request for pedal for a diathermy machine is met with silence and with no verbal acknowledgment. In cases of a delayed actional response, the surgeon is likely to believe that no one has heard him or her. This can create momentary interruptions: in the fragment, the surgeon disengages his gaze from the operating field, repeats the request, and looks around the theatre for a response.

Example 2 is taken from Korkiakangas et al. (2014) and is used in our paper to illustrate the embodiment feature of social interaction. The focus of the qualitative (video) analysis performed in the paper is on one of the most central collaborative tasks during surgical operations, namely the passing of objects, including surgical instruments. A detailed analysis of two surgical cases selected from the video data corpus revealed that two factors affect object transfer: (1) relative instrument trolley position and (2) alignment. In Case A, the trolley is located in front of the scrub nurse and close to the surgeon, so that the scrub nurse and surgeon are standing side by side. In Case B, the trolley is placed behind the surgeon, so that the trolley is positioned between the surgeon and the scrub nurse. The scrub nurse's instrument trolley position (close to versus further back from the surgeon) and alignment (gaze direction) impacts on the communication with the surgeon, and consequently, on the speed of object transfer. The results of the analysis of the speed of passings in the two cases revealed that when the scrub nurse is standing close to the surgeon, and her gaze is directed towards the surgeon's movements, the transfer occurs more seamlessly and faster than when the scrub nurse is standing further back from the surgeon and does not follow the surgeon's movements. The Authors concluded that the smoothness of object transfer can be improved by adjusting the scrub nurse's instrument trolley position, enabling a better monitoring of surgeon's bodily conduct and affording early orientation (awareness) to an upcoming request.

As this section makes clear, the analysis performed on the video extracts briefly described above has been mainly qualitative, involving a detailed examination of the sequence of various interaction practices involving team members during surgical operations. In the next section, we will briefly discuss a tentative coding scheme that may be used to codify video data as relational event data amenable to quantitative social network analysis. We will show how social interaction – with its feature of sequentiality, materiality, and embodiment – can be translated into time-stamped sequences of relational events, and analyzed using relational event models. We direct the reader to Butts (2008; 2009), Brandes et al., 2009, and Butts and Marcum (2017) for a technical description of the relational event framework.

5.2. Coding and then decoding naturally occurring social interaction data

How could these detailed and very context-specific examples help us to make the analysis of social relations richer and closer to the patters of action that are actually observed? What research design and observation scheme would allow us to get "closer to the action" and represent continuous time, multimodal, and embodied social interaction of the kind that the examples we discussed illustrate? In this section, we argue that audio-visual recordings may be considered as a source of raw information that – if properly coded and interpreted – may act as a partial antidote for the stark simplification that social network analysis imposes on the multifaceted world of social relations in teams and small groups. To foreshadow our conclusions, we suggest that audio-visual recording of continuous-time social interaction can produce output data that relational event models (Butts, 2008; Perry and Wolfe, 2013) may take as input. As Leenders et al. (2016) suggest, this class of models is particularly appropriate for studying teams and small group behavior because – as Pilny et al. (2016: 182) put it: "when groups make decisions, manage conflict, or simply communicate with one another, they are engaging in series of ongoing events and changes that occur continuously over time."

Fig. 1 reports one frame extracted from a short video clip (approximately 40 s) showing action of a surgical team composed of five members (consultant [main] surgeon, scrub nurse [nurse 1], circulator [nurse 2], registrar [assisting] surgeon and observer [usually a medical student]) performing a laparoscopic operation.[1] The main event captured by the video involves the main surgeon asking one of the nurses (nurse 2) to administer carbon dioxide ("Gas on please") which is used to inflate the patient's abdomen during laparoscopic (keyhole) surgery. The names of the different team members are reported in the figure. Nurse 2 is not present in the room (she is in a connected preparation room) and will be entering shortly to turn on the gas.

Table 3 reports *one* tentative coding covering 40 s of observed action using the video annotation software BORIS (Friard and Gamba, 2016) frequently used in studies of animal behavior. Our objective is to generate high-quality raw material and create a dataset that is as close as possible to the observation as it happens. Raw material is of high quality to the extent that it maintains all the ambiguity of the observation, rather than resolving such ambiguity through (subjective) classification and aggregation.

Some of the observations take the form of directed interactions connecting a "sender" (or source) to a "receiver" (or target). An example of directed interaction is verbal (e.g., at second 5:107 the main surgeon asks nurse 2 to turn on the gas), and non-verbal communication (e.g., at second 4.603 nurse 1 gazes briefly at the main surgeon). Some other observations are more directly "actional" (e.g., at second 10.103 nurse 2 responds to the request of the main surgeon by entering the scene and turning on the gas). The observation scheme we have devised also allows reconstruction of "states" (e.g., between second 5.855 and 13.105, the surgeon operates on the patient), and "events" (e.g., at second 12.854 the observer sits down). The penultimate column to the right of Table 3 records the distinction between "states" (whose temporal extension is indicated with a "START" and a "STOP" sign) and "events" (whose instantaneity is indicated with a "POINT" sign). We distinguish between states and events based on the duration of the action or interaction relative to the temporal extension of the whole process (Butts and Marcum, 2017). Covariates of "senders" and "receivers" of action can easily be associated with these various behaviors. Covariates can be time-constant, time changing, monadic or dyadic. The information extracted in this way from the audio visual recording could in principle be taken as input by *eventnet* (https://github.com/juergenlerner/eventnet) – a freely available software that supports the analysis of *typed* and *weighted* relational event data (Lerner and Lomi, 2018, 2019).

During the observation period, the main (consultant) surgeon addresses nurse 2 once requesting gas (second 5.107: *"Gas on please"*), and nurse 2 talks to the main surgeon twice when she responds to his request (second 7.101: "Yes, coming") and when she confirms turning on the gas (second 12.366: *"Gas on!"*). Fig. 2 reports the adjacency matrix of the team and the corresponding aggregate "communication network." Clearly, this conventional representation misses much of the details and the complexity of the situation that the team members have experienced during the (approximately) 40 s of action and interaction that we have observed.

Fig. 3 depicts the sequence of observed actions and interactions performed by the main surgeon during the observation period. The vertical axis is defined by the *ethogram* for the main (consultant) surgeon – the inventory of actions performed by the surgeon that are actually observed. The horizontal axis reports time (in seconds). The behavioral sequence for the main (consultant) surgeon includes directed relational communication events ("asks for gas"), occupation of states ("operates on patient"), and events that record actions with material objects ("puts tool down").

Fig. 4 reports the outcome of a similar attempt to reconstruct the behavioral sequence observed for nurse 2. From the audio-video recording that we examined, we see the nurse: (1) responding to the request of the main (consultant) surgeon to turn on the gas valve (communicative relational event); (2) entering the operating room (*actional* event); (3) turning on the valve (*actional* event); (4) confirming her action to the main (consultant) surgeon (communicative relational event), and almost simultaneously (5) leaving the scene (*actional* event). Even in this highly constrained situation, the range of observed behaviors makes the translation of the action in terms of network "ties" problematic, and probably insufficient to render the complexity in the relational texture of the social situation that we observe. It is precisely this relational texture that provides the meaning – and explains – the

[1] The photogram has been modified to preclude identification of the subjects. The video clip is described and analyzed using interactional video analysis in Korkiakangas et al., 2016.

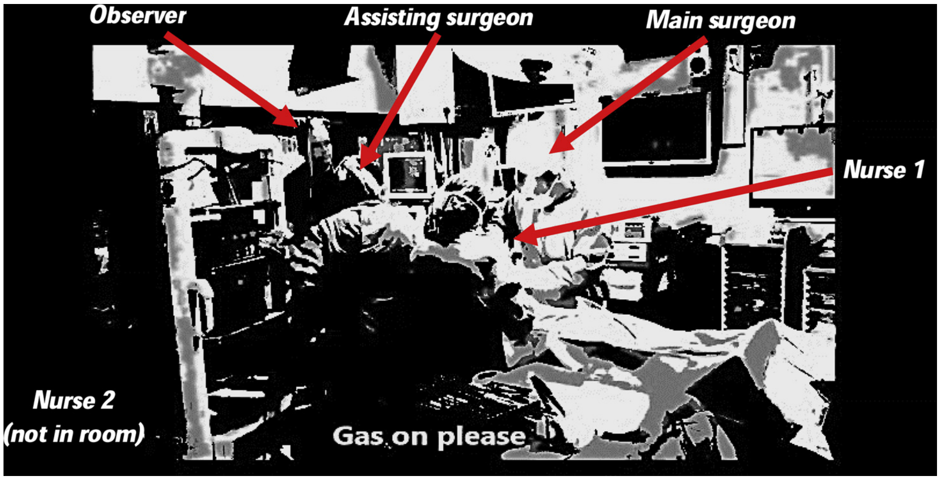

Fig. 1. Frame extracted from a video recording of an operation showing the main surgeon at the operating table asking one of the nurses (Nurse 2) to administer carbon dioxide ("gas") to the patient undergoing surgery. Nurse 2 is not present in the room in this instant (Second 5:107).

Table 3
Complete sequence of directed and undirected behaviors observed during the video recording (highlighted in red are the examples discussed in the main text).

Time	Sender	Behavior	Receiver	Status	Comment
0.6	Main surgeon	Operates on patient	Patient	START	Action (directed)
1.102	Observer	Observes scene		START	Action (undirected)
2.851	Main surgeon	Operates on patient	Patient	STOP	Action (directed)
3.357	Main surgeon	Puts tool down		POINT	Action (undirected)
4.603	Nurse 1	Gazes	Main surgeon	POINT	Interaction
5.106	Assisting surgeon	Gazes	Main surgeon	POINT	Interaction
5.107	Main surgeon	Ask for gas	Nurse 2	POINT	Interaction
5.855	Main surgeon	Operates on patient	Patient	START	Action (directed)
7.101	Nurse 2	Responds	Main surgeon	POINT	Interaction
9.609	Nurse 2	Enters scene		POINT	Action (undirected)
10.103	Nurse 2	Opens gas valve		POINT	Action (undirected)
12.356	Nurse 2	Leaves scene		POINT	Action (undirected)
12.366	Nurse 2	Confirms	Main surgeon	POINT	Interaction
12.854	Observer	Sits down		POINT	Action (undirected)
13.105	Main surgeon	Operates on patient	Patient	STOP	Action (directed)
14.102	Observer	Observes scene		STOP	Action (undirected)
14.510	Main surgeon	Touches patient	Patient	POINT	Action (directed)
26.601	Main surgeon	Talks to team	Nurse 1, Nurse 2, Ass surgeon	POINT	Interaction
28.365	Main surgeon	Gazes	Assisting surgeon	POINT	Interaction
28.615	Main surgeon	Gazes	Assisting surgeon	POINT	Interaction
40.624	Nurse 2	Walks		START	Action (undirected)
42.874	Nurse 2	Walks		STOP	Action (undirected)

	Main_surgeon	Nurse_1	Nurse_2	Assistant	Observer
Main_Surgeon	0	0	1	0	0
Nurse_1	0	0	0	0	0
Nurse_2	2	0	0	0	0
Assistant	0	0	0	0	0
Observer	0	0	0	0	0

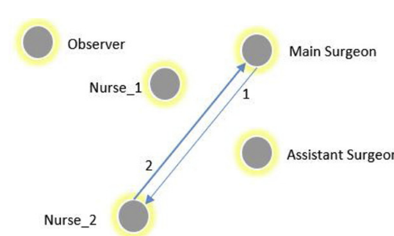

Fig. 2. Valued network of communication relations observed among team members. Adjacency matrix (left panel) and sociogram (right panel). The numbers on the edges refer to the number of communication events observed.

underlying actions that are actually observed.

6. Discussion and conclusions

As Butts observes (2008: 156): "Human activity over short time scales is frequently understood in terms of actions, which can be thought of as discrete events in which one individual emits a behavior directed at one or more other entities in his or her environment (possibly including himself or herself)". This was our starting point in this paper. We noticed that conventional representations of "human activity" in terms of more or less enduring network ties among social agents tend to decouple analytically reconstructed network ties from their internal temporal micro-structure, and hence from social relations as they naturally unfold. We have called attention on the difficulties and new possibilities inherent in collecting and analyzing "naturally occurring data" on the dynamics of social relations.

Inspired by concepts borrowed from conversation analysis (Mondada, 2019), we have discussed how audio-visual recording

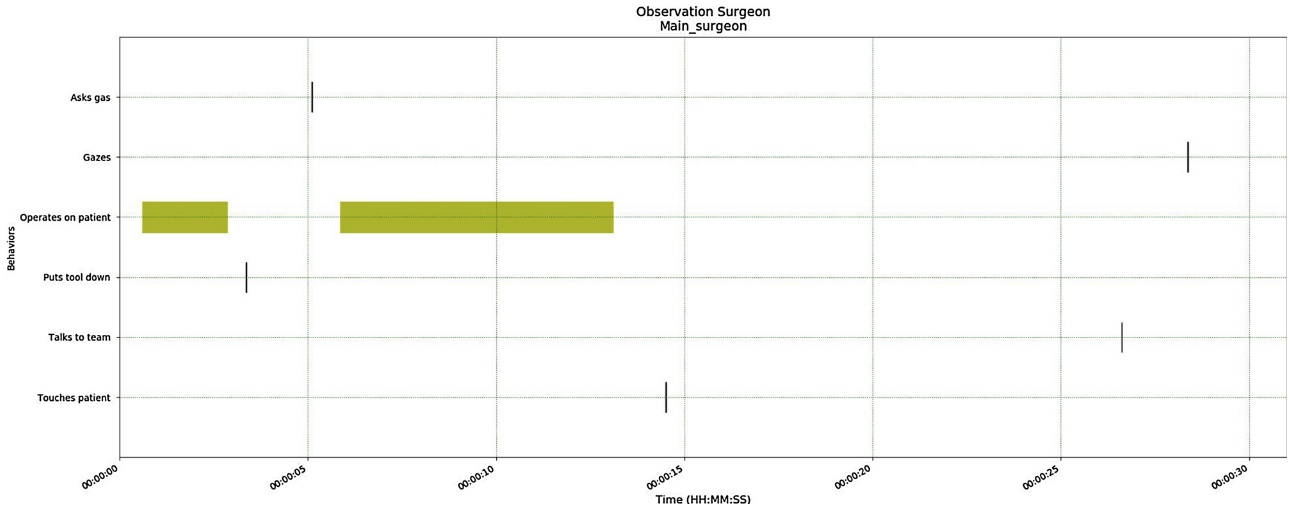

Fig. 3. Sequence of observed actions performed by the main surgeon during the first 40 s of the video. Events are represented as single points in time (thin vertical segments). States occupied by the main surgeon during the period are represented as boxes to convey the sense of temporal extension. The vertical axis represents the space of observed actions for the main surgeon. The horizontal axis is time in seconds.

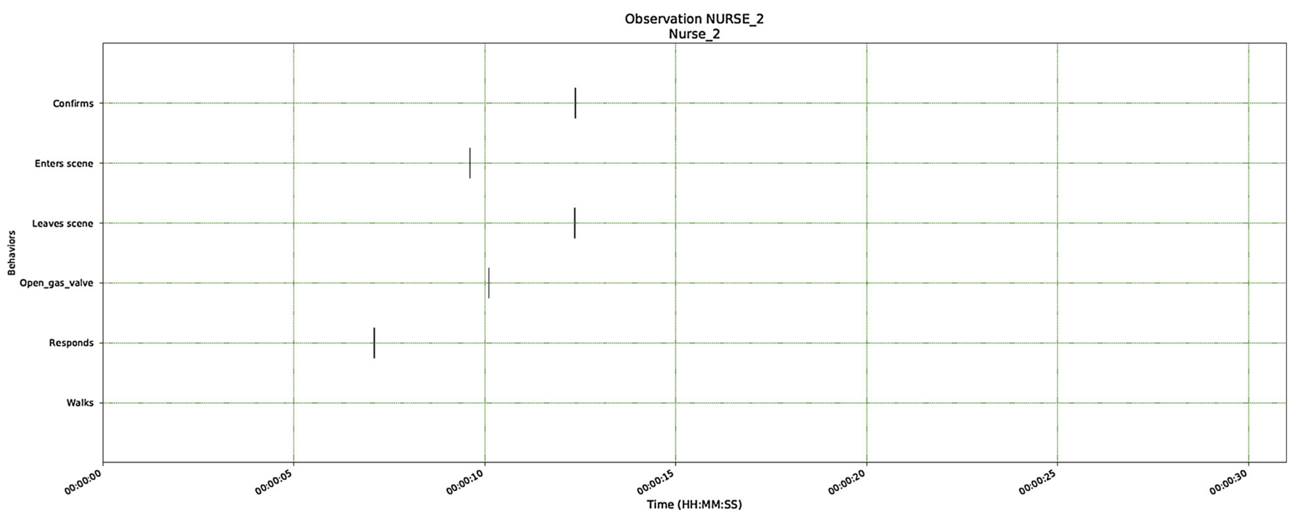

Fig. 4. Sequence of observed actions performed by nurse 2 during the first 40 s of the video. Events are represented as single points in time (thin vertical segments). States occupied by the nurse number 2 during the period are represented as boxes to convey the sense of temporal extension. The vertical axis represents the space of observed actions for nurse 2. The horizontal axis is time in seconds.

technologies may be used to collect continuous-time data that accurately reproduce the micro-structure of social interaction organized around exogenously *given* collective tasks. We have argued that the main advantage of this observation technology is that, in principle, it retains essential information on the temporal sequences of relational events in which social relations are embedded – and out of which they emerge.

We have illustrated how sequences of time-stamped individual behaviors and directed interactions that can be captured by video recordings may provide - through appropriate coding strategies - input data to statistical analysis based on observation of naturally occurring data on social relations (Butts and Marcum, 2017). Recently derived relational event models are now available that afford direct analysis of very large-scale data that are qualitatively similar to those produced by the small-scale illustrative case study we have examined in this paper (Lerner and Lomi, 2019).

We have restricted our discussion to interaction within small task-oriented teams as an empirical setting capable of revealing with particular clarity the value of collecting naturally occurring behavioral data to examine “human activity over short time scales.” Yet, we think that the methodological and substantive implications of our proposal transcend the relatively narrow boundaries of our specific empirical context. The questions we have asked in the context of surgical teams are sufficiently general to be relevant to other types of contexts where task-oriented activities provide the foci for social relations, and where coordination among team members involves multimodal communication flows, that include the handling and exchange of material objects. In restaurant kitchens, for example, teams work under exogenous performance/time constraints, and coordination among the chefs and their assistants involves standardized communication practices, and both non-verbal and gestural communication, as well as interaction with and through a variety of physical objects (Lane, 2014, see particularly chapter 3).

Similar considerations are applicable to the network analysis of sports – an empirical setting that routinely produces continuous-time relational event-like data that are very similar to those we have examined in our illustrative case study (Rodrigues et al., 2017; Wäsche et al., 2017). For example, in a recent paper Mclean et al. (2019) demonstrate how - in the context of football - direct interpersonal relations of verbal communication and indirect relations established between players by passing the ball (the “material object” of interest in that context) may be examined jointly to understand team coordination, and clarify the relational bases of team performance.

Elements of relational materiality and multimodality are also central to our understanding of creative production processes in the arts. In the case described by Basov (2018), for example, different artists share physical spaces, material objects, and ideas. Groups of artists in these commune-like organizations "are usually informal and changeable in structure, flexible in the establishment and severing of social ties" (Basov, 2018: 182). Fluid participation (Cohen et al., 1972) and attrition add elements of complexity to the collection and analysis of network data that were absent from our illustrative case, but that the observational framework we proposed may easily accommodate.

We think our work helps to ask new questions about a number of issues that remain open and that therefore provide valuable raw material for future research. Three, in particular, deserve mention in this concluding section. The first issue concerns the fact that understanding team processes poses unavoidable multilevel issues as what is observed is the behavior of – and interaction among individual participants, but outcomes of interest are typically defined and observed at the team level (Hackman and Morris, 1975). Given the crucial role of effective teamwork and communication between healthcare professionals for patient safety and hospital costs (Bezemer et al., 2016; Korkiakangas et al., 2014), how could the collection and analysis of continuous-time data on interactions within surgical teams be used to improve work practices within operating theatres, and develop a better understanding of the relation between team processes and performance? This is a question that only systematic observation of team performance over time and across settings will be able to address.

The second issue that our work confronts, but leaves open, concerns the tendency to consider behavior observed in video recordings (particularly behavior observed in a single case) as entirely "endogenous," i.e., completely determined by emergent patterns of interaction among participants. This needs not to be the case as observed behaviors may be 'endogenously determined' (like, for example, the interaction within the team arising as a consequence of patients' response during surgery), but also 'exogenously constrained' (like, for example, the surgical routines that do not depend on patients' conditions, and that may derive from prescriptions imposed by evidence-based medicine practices). Clearly, this distinction may be blurred in specific circumstances. For example, where trolley are placed in surgery room and the kind of surgical tools that are used in specific circumstances may seem the outcome of exogenous constraints. In fact, nurses enjoy at least some degree of autonomy in relation to how they position their instruments and the trolleys they are placed on (Korkiakangas et al., 2014). Surgeons have at least some discretion over the choice of surgical instruments needed to perform certain tasks within a procedure. These discretionary choices affect how team members interact during a surgical operation. For example, Korkiakangas et al. (2016) demonstrate that where a scrub nurse places the instrument trolley has a direct impact on the seamlessness of the instrument exchange transaction. Future research will face the delicate task to distinguish between what behaviors, among those observed, are truly exogenous – at least with reference to the time of the process that is being observed.

The third issue that deserves attention concerns the quality and reliability of network data (Marsden, 1990). While clearly not specific to our work (Robins, 2015), problems of data quality and reliability are made more severe by the complex mix of quality and quantity involved in the semi-manual software-assisted data coding procedure that we have developed. We have completely sidestepped issues of reliability of data and coding – issues that are particularly delicate in the coding of data from video recordings (Nassauer and Legewie, 2018). In actual research projects based on video-recorded data, particular care has to be put in coordinating the work of multiple coders to ensure high levels of inter-coder reliability – and a specialized literature is available that addresses this issue (Clarke et al., 2019). The important point here is that issues concerning coding reliability will spill over and affect the reliability of relational event models that may be adopted to analyze the data extracted from video footage. We think that this problem touches upon fundamental, but unresolved problems about the relation between quality and quantity in the observational studies of social networks and social relations (Bellotti, 2014) – problems that are pervasive, but rarely discussed systematically. Central in classic studies of social relations (Killworth and Bernard, 1976; Bernard and Killworth, 1977) – and indeed to the development of social network ideas (Freeman et al., 1987), issues of data quality, ambiguity and ambage now take the back seat to the development of statistical models for networks ties of ever-increasing sophistication. This is unfortunate given the dependence of the statistical results produced by any model on decisions about the data that necessarily precede analysis.

Albeit not exclusively (e.g., Amati et al., 2019), information on continuous time social interaction is frequently extracted from sources of technology-mediated communication data (Butts, 2008; Eagle et al., 2008), that are either publicly available (Lerner and Lomi, 2018), or stored in proprietary platforms (Vu et al., 2015). This strategy greatly reduces concerns of data completeness, quality, and reliability – concerns that are ubiquitous in network-oriented research design, and social network data (Robins, 2015). In the case study we have developed, however, coding was performed semi-manually with the assistance of video annotation software as it is common practice in studies of animal behavior based on naturally occurring data – for recent examples based on BORIS (Friard and Gamba, 2016) see the studies by Iki and Hasegawa (2019) and Holtmann et al. (2019). Clearly, manual and semi-manual video annotation induces the need of multiple raters/coders and the parallel development of a principled process for assessing reliability (Haidet et al., 2009) – a crucial issue that we have deliberately sidestepped in our illustrative example but that will require careful attention in future studies based on audio and video recorded information.

The need to clarify these difficult issues is likely to become more pressing as the capacity to collect, store, retrieve and analyze large quantities of naturally occurring social interaction data continues to increase (Waller and Kaplan, 2018), and the power, efficiency, and sophistication of related video-recording technologies continue to improve (Barakova et al., 2013). However modest in comparison to what current technological developments might be making possible in the near future (Mathur et al., 2012), we hope that our study will contribute to stimulate a discussion on, and around these themes. The new "conversational turn" that the diffusion of video data so clearly invites, can count on well-established theoretical concepts (Mondada, 2019), important precursors within social network analysis (Mische, 2011), and remarkable empirical achievements (Gibson, 2005, 2012).

We hope that the progressive alignment between theoretical ideas that are deep-rooted, but not yet fully articulated, and novel empirical possibilities offered by data collection technologies that are powerful, but not yet fully understood, will help us to bring the study of social relations back into the analysis of social networks.

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